Spreading Activation Approach to Tag-aware Recommenders: Modeling Similarity on Multidimensional Networks

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ABSTRACT

Social tagging systems present a new challenge to the researchers working on recommender systems. The presence of tags, which uncover the reasons of user interests to tagged items, opens a way to increase the quality of recommendations. Yet, there is no common agreement of how the power of tags can be harnessed for recommendation. In this paper we argue for the use of spreading activation approach for building tag-aware recommender systems and suggest a specific version of this approach adapted to the multidimensional nature of social tagging networks. We introduce the asymmetric measure of relevancy (proximity) of two nodes on a multidimensional network as a cumulative strength of (weighted) multiple connections between two nodes, which includes paths and graph-structures connecting the nodes. This metric is also applicable to measure relevancy of two sub-graphs. Spreading activation methods (SAM), which usually employ breadth first search, are an efficient way to define and compute such measure taking into account not only links constituent a path, but the properties of nodes in the path such as node's types and outdegree.

We apply this notion of relevancy to measure similarity of collaborative tagging systems users and present the results of numerical simulation showing that spreading activation methods allow us to discriminate between diverse graph-structures connecting users via resources and tags. We show that the results of simulation are stable w.r.t. the variation of parameters of spreading activation algorithm used in our experiment.

Categories and Subject Descriptors

H.3.4 [**Information Storage and Retrieval**]: Systems and Software – *information networks*; H.3.5 [**Information Storage and Retrieval**]: Online Information Services – *data sharing.*

General Terms

Algorithms, Measurement, Performance, Experimentation.

Keywords

Tagging, relevancy propagation, spreading activation, graph-based mining, structural cohesion, CiteULike.

1. INTRODUCTION

Social tagging systems introduced new challenges to the well-established area of recommender systems. While the majority of content based, collaborative, and hybrid recommender approaches were created for a bi-modal world of items and users (connected by rating incidents), social tagging systems present a more complicated world of users, items, and tags (connected by tagging incidents, also known as tagging instances). While some early works attempted to treat the problem of recommendation in social tagging systems in an "old way", basically ignoring the tags, the majority of researchers in this new area argued that tags are vital for successful recommendation in this new domain and called for tag-aware recommenders. They argued that on one hand, tags can compensate the loss of ratings (which are not available in most social tagging systems), while on the other hand, tags can make recommendation more precise because they provide not only the information of what items are of interest to a user, but also why they are of interest [8,14,20,26].

Despite the common agreement that tags should be used as a successful recommender component of a social tagging system, there is no agreement on how it should be done. As a result, a multitude of approaches emerged just over the last three years. Roughly, these approaches can be classified as an extension of either content-based or collaborative filtering approaches. The former group emphasizes connections between items and tags treating tags as an alternative (or additional) way to describe items and establish a profile of user interests [9, 15]. The latter group emphasizes connections between users and tags to establish a better similarity between users in a social tagging system [25, 26].

We argue than inherently networked nature of social tagging systems calls for some alternative recommender approaches, which are not just simple extension of either content-based or collaborative technologies. A successful recommender approach for this new context should fully employ the complex network structure of a typical social tagging system and use all kinds of links: user-tag, item-tag, user-item. We think that the most promising in this context is the spreading activation approach. This approach has been originally developed in the field of cognitive psychology [3] to model human brain and later explored in the context of information retrieval [7].

The power of spreading activation approach was recognized in the area of recommenders and other personalized systems as well; however, so far these approaches form just a small minority. The problem is that the traditional user-item universe does not provide a sufficiently rich network for spreading activation technology. Thus most of known recommenders based on spreading activation were built for context where an additional network can be formed such as a hypertext network for Web page recommendation [17] or a network of entities and concepts in semantically enriched recommenders [4, 12, 18].

We believe that social tagging systems will provide a new promising context as well as new challenges for recommenders based on spreading activation. What we consider as the main challenge is the multidimensional nature of a typical social tagging network. Almost all existing applications of spreading activation for personalization and recommendation operated in relatively homogeneous kinds of networks with 1-2 kinds of nodes and one kind of links. In contrast, even a simplified social tagging network, where each tagging event is represented by a group of three links (user-tag, item-tag, and user-item) includes three types of nodes and three types of asymmetric links. This organization requires some more sophisticated spreading activation approaches.

Our paper attempts to address this challenge by introducing the asymmetric measure of relevancy (proximity) of two nodes on a multidimensional network as a cumulative strength of (weighted) multiple connections between two nodes which includes paths and graph-structures connecting the nodes. This metric is also applicable to measure relevancy of two sub-graphs. Spreading activation methods, as breadth first search, is an efficient way to define and compute such measure taking into account not only links constituent a path, but the properties of nodes in the path such as node's types and outdegree.

We apply this notion of relevancy to build a tag-aware approach to measure similarity between users in collaborative tagging systems. The paper presents the results of a numerical simulation showing that spreading activation algorithms allow discriminating the degree of connectivity of users between certain graph-structures connecting users via resources and tags. We demonstrate that the results of the simulation are stable w.r.t. the variation of parameters of the spreading activation algorithm used in our experiment.

The rest of the paper is organized as follows. In section 2 we first provide a short overview of related work focusing on the use of spreading activation methods (SAM) to propagating and redistributing relevancy. We also theorize about desired properties of relevancy propagation on multidimensional network models of Web. 2.0 data needed to create efficient and scalable recommender systems.

In section 3 we render a formal model of folksonomies (tripartite hypergraph) as a multidimensional network with four types of nodes corresponding to users, resources, tags and instances of tagging. In section 4 we present the results of numerical simulation. Finally, section 5 describes the conclusions and future work

2. RELATED WORK

2.1 Overview of Relevancy Propagation Using Spreading Activation Methods

In neurophysiology interactions between neurons are modeled by way of activation which propagates from one neuron to another via connections called synapses to transmit information using chemical signals. The first spreading activation models were used in cognitive psychology to model these processes of memory retrieval [5, 3]. This framework was later exploited in Artificial Intelligence as a processing framework for semantic networks and ontologies, and applied to Information Retrieval [2, 7, 19] as the result of direct transfer of information retrieval ideas from cognitive sciences to AI. In other domain, [27] created spreading activation models for trust propagation on the Web.

In [21] and [23] authors work with the notion of the relevancy of ontological concepts to a free text. They propagate relevancy of the concepts explicitly mentioned in a document to other ontological concepts using a spreading activation algorithm. Their algorithm works in such a way, that after short number of iteration the topical foci of a cohesive coherent text become the most activated concepts (even if they were not explicitly mentioned in the text).

In [22] authors summarize their experience in creating graph-based related item recommender for activity centric environment on a Nepomuk Social Semantic Desktop [24]: relevancy of a "pile" of nodes representing resources and concepts is propagated to other nodes. Authors in [22] conclude that as a graph-mining technique, spreading activation combines fuzzy clustering and soft inferencing, and therefore might be suitable for relevancy propagation. Propagation should lead to discovery of new nodes which have short length paths to many (if not all) nodes from the initial set. In other words, newly discovered nodes should minimize the "distance" to the initial set of nodes, i.e., nodes which might be considered as potential centroids of strong clusters induced by the initial conditions. Since partitioning of the nodes according to these clusters is not needed, processing of polycentric queries [22] for related item recommendation could be done using soft clustering methods. On the other hand, relevancy propagates through links. an alternative view on the related item recommendation is that newly discovered nodes must be connected to the initial conditions by particular types of directed links. Therefore, propagation of relevancy might be interpreted as fuzzy inference.

In [23], the authors go further in analyzing SAM as a very general class of iterative algorithms for relevancy propagation, local search, relationship/association search, and computing of dynamic local ranking. Authors indicate that the same iterative algorithms were used long before in numerical simulation in physics, mechanics, chemistry, and engineering sciences. Hence, the algorithm is quite polymorphic: "Using the same iterative algorithm, with one set of parameters one can emulate heat transfer; with another set of parameters the same algorithm will show us the behavior of oscillating strings".

2.2 Spreading Activation in Recommender Systems

Spreading activation approach as a technology for recommendation in various kinds of networks belongs to a broader group, which is typically referred to as graph-based approaches for recommendation. In addition to several recent papers mentioned in the introduction, which explicitly use spreading activation to build recommender systems, we can a few other examples of using various graph-based approaches. In [1], the authors presented a theoretic approach where users are modeled as nodes in a directed graph and the directed links represent how representative is a user of another user's behavior. In [11], the authors use spreading activation to deal with the sparsity problem in collaborative filtering. They try to tackle the problem finding transitive relationships by comparing three different methods on a bipartite graph which represented consumer-product interactions. Other interesting approach was the one presented in [10], where the authors propose a constrained spreading activation algorithm having good results compared with a traditional memory-based approach over a small subset of the Movie Lens data set. These approaches show the potential of spreading activation to be used on recommender systems, but they don't take into account the nature of multidimensional networks, such as folksonomies derived from collaborative tagging systems, where different types of nodes, links and relationships can have a strong influence in the design of the algorithms.

2.3 Propagating Relevancy on Multidimensional Web 2.0 Networks

We focus on the applications of SAM to measure similarity between the users of collaborative tagging systems modeled as multidimensional networks. Indeed, we treat graph-based "similarity" of users as a particular case of "relevancy" of nodes on multidimensional networks. In this subsection we provide consideration on which properties of a generic class of spreading activation algorithms are suitable methods for modeling relevancy propagation.

The general inspiration behind using graph-based methods to model relevancy (energy, trust, risk, etc.) propagation on networks is probably the same in many domains: the relevancy is treated as a kind of energy which might be "injected" into some nodes, and propagated through links to other nodes: "… the closer node x to the injection source s, and the more paths leading from s to x, the higher the amount of energy flowing into x in general" [27]. Therefore, spreading activation methods (SAM), which usually employ breadth-first search), are an efficient way to propagate relevancy. Since according [23] SAM is a broad class of algorithms, the choice of algorithm's parameters is crucial and can be done taking into account the nature of the target application.

First of all, Web 2.0 data could be accurately modeled only by multidimensional networks. For instance, formal model of a folksonomy as tripartite hypergraph [13] converted to network representation, has four types of nodes: users, resources, tags, instances of tagging. The shortest possible path between two folksonomy users has the length four (for instance, user1- instance of tagging1- tag - instance of tagging2 - user2). As compared to trust propagation in heterogeneous networks, the amount of relevancy flowing from one node to another should depend not only on types of links, but on properties on nodes in paths. Connections via resources might be more important than connections through tags. In our future work we are going to exploit what [23] calls "the importance of nodes", but one property of nodes which should significantly affect the propagation, can be immediately inferred from the local topology of the network, namely from the number of outcoming links from a node. Ambiguous and top popular tags might be linked to big number of tag instances and big number of users. Intuitively, connections via such tags should provide less (if any) contribution to the similarity of users as compared to the connections through less popular tags.

In [27], the authors assume that nodes with the higher shortest path distance from the injection source should be accorded less trust in general. This property of trust propagation is probably not applicable to propagating relevancy to measure similarity of folksonomies users. Moreover, we suggest that for many applications on multidimensional networks the length of the shortest path might have positive correlation with the relevancy, but is probably much less important and is too coarse-grained measurement compared to trust propagation.

A final observation on relevancy propagation on multidimensional networks: we don't assume that all (or many) aspects of such propagation can be properly understood in terms of paths. We assume that there might be structures (like network B on the Fig. 1), which might significantly affect the relevancy propagation.

3. THE ALGORITHM

The algorithm we used in our experiment in general follows [23] and employs iterative steps where activation is propagated between neighbor nodes. To facilitate comparison of activation distributions on the same or different networks and to account for dissipation of activation caused by list purging step in spreading activation, we introduce the step of normalization (calibration).

A multidimensional network can be modeled as a directed graph, which is a pair $G = (V,E)$ where

V – is the set of vertices v_i

E – is the set of arcs e_j

init: $E \rightarrow V$, is the mapping that provides initial nodes for arcs

term: $E \rightarrow V$, is the mapping that provides terminal nodes for arcs

imp – is importance value of arcs and nodes.

w – "weights"

$F(E)$ – is the "activation" real valued function

The algorithm has the following steps

Initialization

Sets the parameters of the algorithm, network, and initial $F(E)$ as a list of non-zero valued nodes V_n

Iterations

a. List Expansion.

b. Recomputation: The value at each node in the list is recomputed based on the values of the function on nodes which have links to the given node and types of connections.

c. List Purging: We exclude the nodes with the values less than a threshold.

d. Conditions Check To Break Iterations.

Normalization

Linear scaling up or down the numerical values of the activation level of all nodes in the list of activated nodes to satisfy some conditions of activation conservation

Output

The list of nodes (value of the function after spread of activation) ranked according F values.

Recomputation step is as follows:

- We have the list of nodes Vn.
- **Input/Output Through Links Computation.**

- – For each node v we compute the input signal to each arc e, such that init(e)=v. This computation can be based on the value F(v), the outdegree of a node etc. For instance, if the node v has n outgoing arcs of the same type, each arc e might get input signal:

$$I(e) = F(\text{init}(e)) \cdot (1 / \text{outdegree}(v)\ \hat{}\text{beta})$$

  where beta might be equal to 1. It could be also less than one, in which case the node v will propagate more activation to its neighbors than it has. (This might be fine for some applications).

- – When the signal ("activation") passes through a link e, the activation usually experiences decay by a factor $w(e)$:

$$O(e) = I(e) \cdot w(e)$$

- **Input/Output Of Node Activation**
  - – Before the pulse, the node v has the activation level $F(v)$.
  - – Through incoming links v get more activation:

$$\text{Input}(v) = \Sigma\ O(e)$$

    for all links e such that init(e) $\in V$n, term(e) = v.

  - – By dissipating the activation through outgoing links, the node v might lose activation:

$$\text{Output}(v) = \Sigma\ I(e)$$

    for all links e such that init(e) = v, term(e) $\in V$n

- **Computation Of New Level Of Activation**

$$\text{Fnew}(v) = F(v) + \text{Input}(v)$$

To apply spreading activation to measure "similarity" of two nodes on a network, we put the initial activation 1.0 at the first node, and measure the activation at the second node after certain number of iterations.

4. EXPERIMENTS

To apply graph-based mining on web 2.0 data we model the data by a multidimensional network (where nodes and links are typed, and links are "weighted").

In our experiments we use three networks representing instantiations of collaborative tagging systems. Each of these networks has two actors (A1 and A2), two resources (R1 and R2), and four instances of tagging (I1, I2, I3 and I4). For instance, the network A on the figure 1 has the instance of tagging *I1* with links to the actor *A1*, the resource *R1*, and the tag *T*; this sub-network shows that the actor *A1* used the tag *T* for the resource *R1*. Correspondingly, the links from the instance *l2* show that the actor *A1* used the tag *T* for the resource *R2*. The instances *I3* and *I4* show tagging for the user *A2*. The network *A* represents the situation where both actors used the same tag for both resources.

In the implementation of our algorithm, each of these networks is modeled by a directed graph, where for each link we create two reciprocal arcs. In each experiment we set initial activation at the node corresponding to the actor A1 and after several iterations of the algorithm we compute the "similarity" of actors A1 and A2 using the method described in 3.

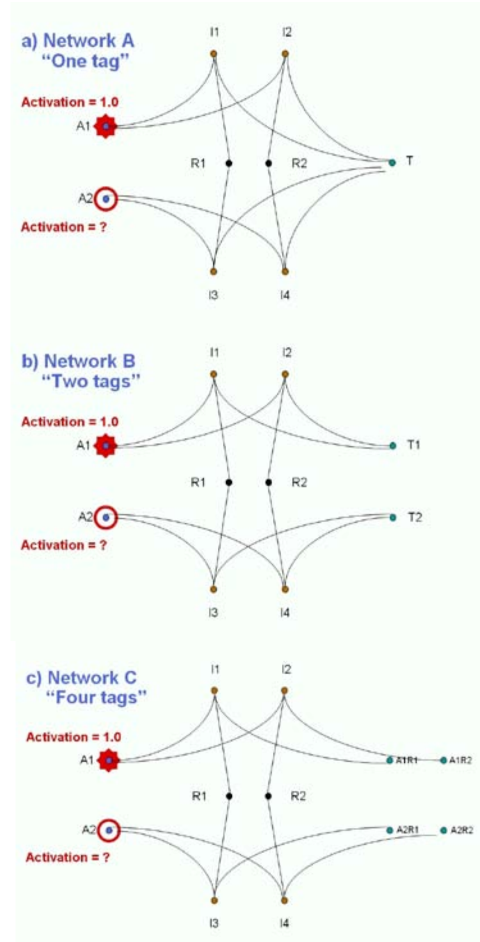

Figure 1. Three networks modeling instantiations of collaborative tagging systems.

In [23], the authors view SAM in terms of graph-mining algorithms as a technique for soft clustering. The major parameters of SAM affecting "the scale" of the phenomena to be discovered are signal decay and number of iterations (larger number of iterations and low decay are needed to discover "bigger" clusters). Since Web 2.0 applications are at the focus of this paper, we run the experiments varying these two parameters. Our target was to find regions of the parameters which allow us consistently to capture structures like that on the Fig.1.

In this paper, we use SAM as a link analysis algorithm for local ranking, in the same way as PageRank algorithm is used for global ranking [28]. The major difference between them is that PageRank iteratively redistributes the relevancy measure which is initially set to each node of the network, while we use SAM to iteratively redistribute the relevancy measure (the activation) from one (or more) nodes sometimes referred to as "seeds".

Diameter of graphs B, and C is 6, with the number of iterations less than 6 the activation from a node on a network will not necessarily reach all the nodes. The limit distribution (distribution of the activation after a number of iterations big enough), produced by SAM, in general does not depend on the choice of the initial seed. This behavior gives us the estimate that local ranking, which is highly sensitive to sub-graphs with the diameter

6, could be achieved when the activation will be redistributed on such sub-graphs several times which amounts roughly to 12-48 iterations.

Our underlying common-sense assumption is that connectivity of A1 and A2 is bigger in the network A than in B and C; and that the connectivity of A1 and A2 in the network B is bigger than in the network C. In other words, if we denote the final activation of the node *v* in the network configuration *X* as *x(v)*, we would expect that sensible local ranking results should satisfy inequality:

$$a(A2) > b(A2) > c(A2) \qquad (1)$$

The shortest path between the nodes A1 and A2 equals to 4 in the network A, and to 6 in networks B and C. So the first part of the inequality is easily achieved with any parameters of the algorithm (provided that the number of iterations is not less than 3). To investigate how the algorithm can discriminate between configurations B and C we introduce the *network discrimination factor* as

$$NDF = \frac{b(A2) - c(A2)}{a(A2) - c(A2)} \qquad (2)$$

We computed the *NDF* ranging the number of iterations from 1 to 50, and the decay factor from 0 to 1. Figure 2 shows the results, where the X axis represents number of iterations, the Y axis the decay factor, and the Z axis the network discrimination factor.

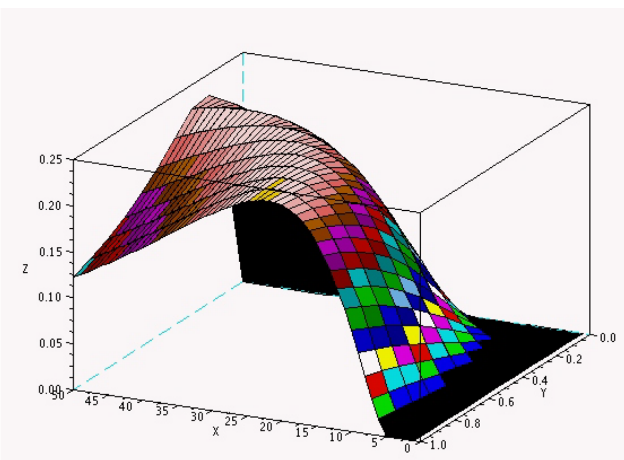

Figure 2. Results of the NDF experiment. Axis *X* shows iterations, axis *Y* decay values, and axis *Z* the NDF.

The results in figure 2 show that we maximize the NDF when running our spreading activation algorithm with a decay factor between 0.8 and 0.9, and 24 iterations. Additionally, the plot shows stable results for our algorithm, which suggests that selecting values in close ranges will not return unexpected or random activation values.

We have shown that on small networks SAM might be used to measure similarity between users. It is part of our future plans to show that on big multidimensional networks representing Web 2.0 data activation initiated at one of the nodes could be kept flowing within strong clusters induced by the initial set of activated nodes (because of high degree of clustering); and therefore the results could be generalized to real-world data.

5. CONCLUSIONS AND FUTURE WORK

Our paper argued for the use of spreading activation as a recommendation mechanism in multidimensional networks produced by collaborative tagging systems. We introduced the new network-based asymmetric measure of relevancy of two nodes on a multidimensional network and applied it to build a tag-aware approach to measure similarity between users in collaborative tagging systems. While it is just one of several possible ways to use spreading activation in collaborative tagging context, we consider it as the best way to start. As demonstrated by the stream of recent works, calculating similarity between users is a component of the recommendation process where the use of tags can provide a most valuable impact [25, 26].

The results of our experiments show that our metrics can be used to differentiate activation levels on different network configurations and they also show a stable behavior when input parameters are changed. These results lead us to pass to the next step on our research on this bottom-up approach, which is to prove that our results are repeatable in large scale networks. We are currently running our experiments on real social network data that we have collected from the social bookmarking service CiteUlike.

In this paper we presented applications of spreading activation methods to local ranking on small networks. We didn't prove yet that the same "good" properties hold true when the algorithm runs on massive networks. However, multidimensional networks which model web 2.0 data and processes usually exhibit small world phenomena properties, which include small average distance and clustering effect. According to [23] spreading activation might be considered as a method for soft clustering. Intuitive justification of the use of spreading activation for ranking is the same as for the PageRank algorithm [28]: a node can have a high rank if there are many nodes that point to it, or if there are some nodes that point to it and have a high rank. On each iteration strongly activated nodes continue to support the high level of activation of nodes to which they have outcoming links, while nodes which have little connection with strongly activated nodes eventually lose their activation. Therefore, even if constrained spread of activation from one node might in several iterations reach significant portion of the network (small average distance), strong level of activation will be supported mainly in strong clusters induced by the node.

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